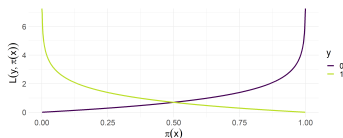
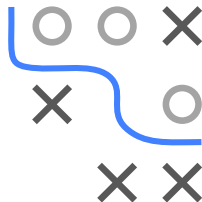


# Introduction to Machine Learning

## Optimal constant model for the empirical log loss risk (deep-dive)



### Learning goals

- Derive the optimal constant model for the binary empirical log loss risk
- Derive the optimal constant model for the empirical multiclass log loss risk

# BINARY LOG LOSS: EMP. RISK MINIMIZER

Given  $n \in \mathbb{N}$  observations  $y^{(1)}, \dots, y^{(n)} \in \mathcal{Y} = \{0, 1\}$  we want to determine the optimal constant model for the empirical log loss risk.

$$\arg \min_{\theta \in (0,1)} \mathcal{R}_{\text{emp}} = \arg \min_{\theta \in (0,1)} - \sum_{i=1}^n y^{(i)} \log(\theta) + (1 - y^{(i)}) \log(1 - \theta).$$



## BINARY LOG LOSS: EMP. RISK MINIMIZER / 2

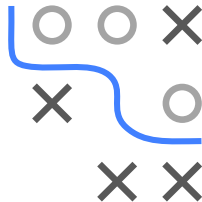
The minimizer can be found by setting the derivative to zero, i.e.,

$$\frac{d}{d\theta} \mathcal{R}_{\text{emp}} = - \sum_{i=1}^n \frac{y^{(i)}}{\theta} - \frac{1 - y^{(i)}}{1 - \theta} \stackrel{!}{=} 0$$

$$\iff -\sum_{i=1}^n y^{(i)}(1-\theta) - \theta(1-y^{(i)}) \stackrel{!}{=} 0$$

$$\iff -\sum_{i=1}^n \left( y^{(i)} - \theta \right) \stackrel{!}{=} 0$$

$$\Rightarrow \hat{\theta} = \frac{1}{n} \sum_{i=1}^n y^{(i)} \in (0, 1) \checkmark \text{(assuming both labels occur).}$$



## MULTICLASS LOG LOSS: EMP. RISK MINIMIZER

Given  $n \in \mathbb{N}$  observations  $y^{(1)}, \dots, y^{(n)} \in \mathcal{Y} = \{1, \dots, g\}$  with  $g \in \mathbb{N}_{>1}$  we want to determine the optimal constant model  $\theta \in (0, 1)^g$  for the empirical log loss risk

$$\begin{aligned} \arg \min_{\theta \in (0,1)^g} \mathcal{R}_{\text{emp}} &= \arg \min_{\theta \in (0,1)^g} - \sum_{i=1}^n \sum_{j=1}^g \mathbb{1}_{\{y^{(i)}=j\}} \log(\theta_j) \\ \text{s.t.} \quad &\sum_{j=1}^g \theta_j = 1. \end{aligned}$$

We can solve this constrained optimization problem by plugging the constraint into the risk (we could also use Lagrange multipliers), i.e., we replace  $\theta_g$  (this is an arbitrary choice) such that  $\theta_g = 1 - \sum_{j=1}^{g-1} \theta_j$ .

## MULTICLASS LOG LOSS: EMP. RISK MINIMIZER / 2

With this, we find the equivalent optimization problem

For  $j \in \{1, \dots, g-1\}$ , the  $j$ -th partial derivative of our objective

where  $n_k$  with  $k \in \{1, \dots, g\}$  is the number of label  $k$  in  $y$  and we assume that  $n_k > 0$ .

## MULTICLASS LOG LOSS: EMP. RISK MINIMIZER / 3

For the minimizer, it must hold for  $j \in \{1, \dots, g-1\}$  that

$$\frac{\partial}{\partial \theta_j} \mathcal{R}_{\text{emp}} \stackrel{!}{=} 0$$

$$\iff -n_j\theta_g + n_g\theta_j \stackrel{!}{=} 0$$

$$\Rightarrow \sum_{j=1}^{g-1} (-n_j \theta_g + n_g \theta_j) \stackrel{!}{=} 0$$

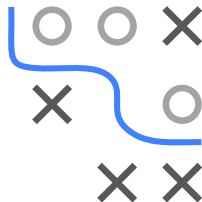
$$\Longleftrightarrow -(n - n_g)\theta_g + n_g(1 - \theta_g) \stackrel{!}{=} 0$$

$$\Longleftrightarrow -n\theta_g + n_g \stackrel{!}{=} 0$$

$$\Rightarrow \hat{\theta}_g = \frac{n_g}{n} \in (0, 1) \checkmark$$

$$\Rightarrow \forall j \in \{1, \dots, g-1\} : \quad \hat{\theta}_j = \frac{\hat{\theta}_g n_j}{n_g} = \frac{n_j}{n} \quad \in (0, 1) \checkmark.$$

$$\left(\Rightarrow \sum_{j=1}^{g-1} \hat{\theta}_j = 1 - \hat{\theta}_g = 1 - \frac{n_g}{n} < 1 \checkmark\right)$$



# CONVEXITY

Finally, we check that we indeed found a minimizer by showing that  $\mathcal{R}_{\text{emp}}$  is convex for the multiclass case (binary is a special case of this):

The Hessian of  $\mathcal{R}_{\text{emp}}$

$$\nabla_{\theta}^2 \mathcal{R}_{\text{emp}} = \begin{pmatrix} \frac{n_1}{\theta_1^2} & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \frac{n_{g-1}}{\theta_{g-1}^2} \end{pmatrix}$$

is positive definite since all its eigenvalues

$$\lambda_j = \frac{n_j}{\theta_j^2} > 0 \quad \forall j \in \{1, \dots, g-1\}.$$

From this, it follows that  $\mathcal{R}_{\text{emp}}$  is (strictly) convex.

